ADVANCEMENT AND IMPLEMENTATION OF IMAGE FUSION SCHEME UNDER MULTI SCALE DECOMPOSITION THROUGH SIMULATION

Research Protocol / Synopsis
For Registration For Ph.D. Program
Submitted by

Gaurav Choudhary
(University Roll No. 20PHEN024)

JECRC™
UNIVERSITY
BUILD YOUR WORLD

Under the Guidance of
Dr. Dinesh Sethi
Associate Professor
Department of Electronics and Communication Engineering,
JECRC University, Jaipur

2021

JECRC University, Jaipur

CERTIFICATE

JECRC™ UNIVERSITY
BUILD YOUR WORLD

This is to certify that the **Research Synopsis** entitled **"ADVANCEMENT AND IMPLEMENTATION OF IMAGE FUSION SCHEME UNDER MULTI SCALE DECOMPOSITION THROUGH SIMULATION"** by **GAURAV CHOUDHARY,** submitted in fulfillment of the requirement for the Ph.D. in **ELECTRONICS AND COMMUNICATION ENGINEERING** under the **School of Engineering** of **JECRC University, Jaipur**, during the academic year 2021-24, is a bonafide record of work carried out under my guidance and supervision. The matter embodied in this **Research Synopsis** is **original** in character and has not been submitted to any other University for the award of any other degree or diploma.

Date:

(Signature of Guide)

Dr. Dinesh Sethi
Associate Professor
Department of ECE
School of Engineering
JECRC University, Jaipur

Research Scholar's Basic Information

1. Name of the Candidate: **GAURAV CHOUDHARY**
2. Father's Name: **CHHATTAR SINGH CHOUDHARY**
3. Mother's Name: **SANTOSH CHOUDHARY**
4. Registration No.: **20PHEN024**
5. Date of Birth: **22/07/1990**
6. Permanent Address: **61, Bhagwati Nagar 2, Kartarpura, Jaipur**
7. Address for Correspondence: **Same as Permanent**
8. Email: **gauraver.jpr@gmail.com/gaurav.20phen024@jecrcu.edu.in**
9. Mobile No.: +91-9950988698/+91-9079349847
10. PG Degree Title: **M.Tech (ECE),** CGPA: **7.79/10**
11. Title of Research Plan: **Advancement And Implementation Of Image Fusion Scheme Under Multi Scale Decomposition Through Simulation**

Date: Signature of the Candidate

Certificate..... *i*

Research Scholar's Basic Information..... *ii*

Table of Contents..... *iii*

Table of Contents

S.No.	Topic	Page
1	Introduction	1-2
2	Literature Review	3-12
3	Justification For Selection of Research Area	13
4	Objectives of the Study	14
5	Methodology	15-18
6	Expected Outcomes	19
7	Work Plan/Time Lines	20
8	References	21-26

1. Introduction

Image fusion is the process of improvement in the resolution of an image in order to facilitate visual communication. In image fusion, two or more images are blended to create a single fused image containing more visual information than each original image (Chaudhuri and Kotwal, 2014; Mitchell, 2015; Xiao *et al.*, 2020). This idea is applied to a wide variety of areas, including computer vision, digital photography, medical science, concealed weapon detection, military navigation, robotics, and visible-infrared imaging. Thus, image fusion is a significant area of research due to its prevalence in various applications.

Despite the fact that image fusion research began a long time ago, numerous contributions are still being made due to the fact that it is used in a wide range of applications, as previously mentioned. This point is demonstrated in Fig. 1, where the number of publications (original articles, review articles, books etc.) published year over year clearly illustrates an upward tendency in this discipline. This was accomplished by searching for the keyword "image fusion" in the Web of Science database, with only minor modifications/sorting in the year selection. As seen in this figure, considerable growth has been shown for the last ten years. It is because of the rapid development in signal processing or image processing techniques such as discrete wavelet transform (DWT) (Van Fleet, 2019), discrete cosine transform (DCT) (Jiang and Kim, 2021), fractional Fourier transform (FFT) (Saxena and Sharma, 2018), Hilbert vibration decomposition (HVD) (Feldman, 2008; Saxena and Sharma, 2016), higher-order singular value decomposition (Liang *et al.*, 2012; Xiao *et al.*, 2020), sparse representation (Thiagarajan *et al.*, 2014) and various other adaptive signal/image decomposition methods (Feng, Zhang and Zuo, 2017). In addition, the field of artificial intelligence in which machine learning and deep learning have recently gained much attention. The same, especially in deep learning, has also been attempted in this domain since 2017, making it more relevant for future aspects (Zhang *et al.*, 2021).

In this research plan, a tentative technique/approach with multiple objectives is proposed after taking into account the methods that have been already published in the literature. It is anticipated that the projected process would give better/comparable outcomes to the existing ways already provided. As a result, the following is the structure of this research plan: As a starting point, in Section 2, a quick and precise review of the literature, including the fundamentals and applications of image fusion, is provided. Following that, in Section 3, the justification for the selection of the

research area is discussed. Then, in Sections 4 and 5, many objectives of this study and the methodology that will be adopted are discussed in further detail. Finally, a description of the proposed outcomes of this research strategy with a work plan is concluded.

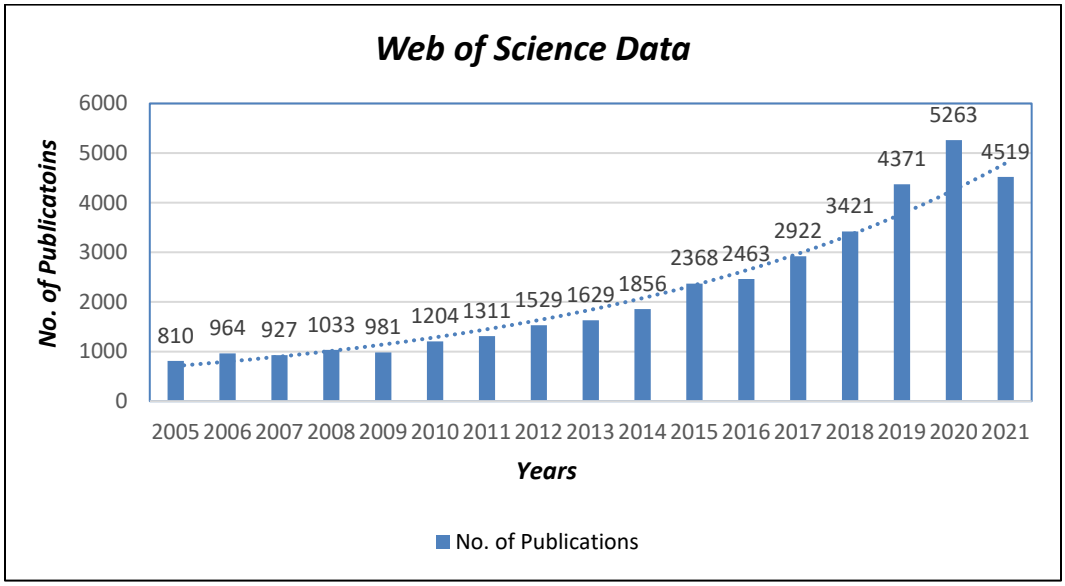


Fig. 1. No. of Publications (Data collected from Web of Science) (Image fusion (Topic) – 40,076 – Web of Science Core Collection)

2. Literature Review

In this part, a careful review of existing image fusion techniques has been provided. Before that, the key concepts and fundamentals of image fusion and the different applications are explained, which will serve as a foundation for comprehending the issue.

2.1. Image Fusion Fundamentals

2.1.1. Basic Overview

Image fusion is primarily comprised of eight essential stages, which are as follows (Xiao *et al.*, 2020): 1) Image acquisition, 2) Pre-processing, 3) Image registration, 4) Image fusion, 5) Post-processing, 6) Fusion-performance evaluation, 7) Storage, and 8) Display

As seen in Fig. 2, source images are acquired using single or multiple sensors in the initial stage. Following that, noise or artifacts introduced in the source images during acquisition will be removed in pre-processing step. After that, the image registration process assists the image to be aligned according to the coordinate system. In the next step, the fusion process is performed according to the different criteria and principles involved. Further, the fusion process proceeds according to the required application in which fusion performance may be observed by computing some standard objective fusion metrics. In addition, post-processing may be required as per the application. Finally, the display/storage stage is used to display the results of the outcomes of the fusion process.

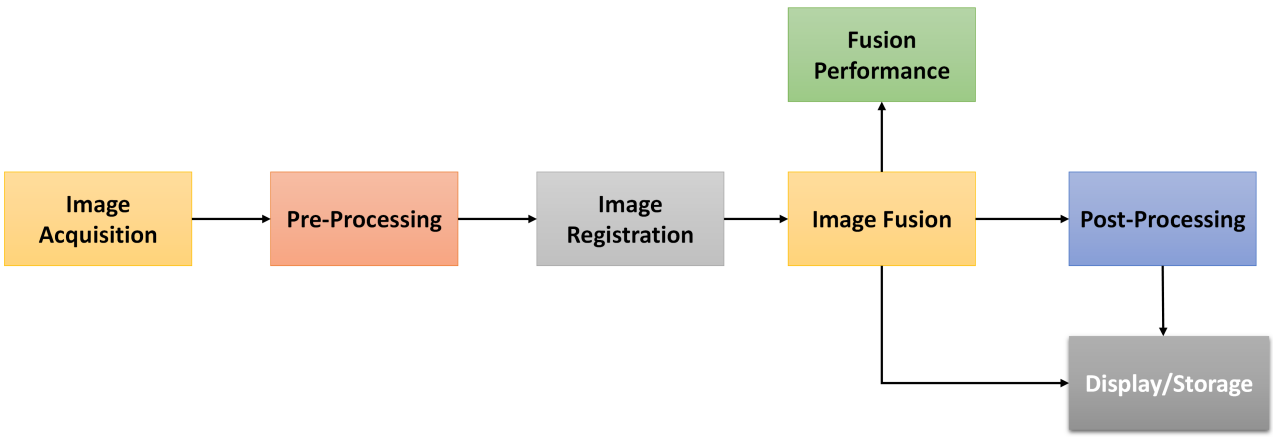


Fig. 2. (Xiao et al., 2020) Essential stages in the process of Image Fusion

2.1.2. Information Transfer, Visual Artifacts and Fusion Loss

The essential principle of image fusion can be understood using a Venn diagram from set theory, as illustrated in Fig. 3. As seen from this figure, two source images X and Y, are the two different sets and set F indicates the fused image obtained by integrating these two source images. Ideally, this combined image should contain all the information from source images. However, only the essential and sufficient information will be transmitted, and data loss of the source image may occur concurrently with the fusion process (Xiao *et al.*, 2020). Additionally, the fusion process may inject additional information known as "fusion artifacts" into the fused image, as seen in the figure.

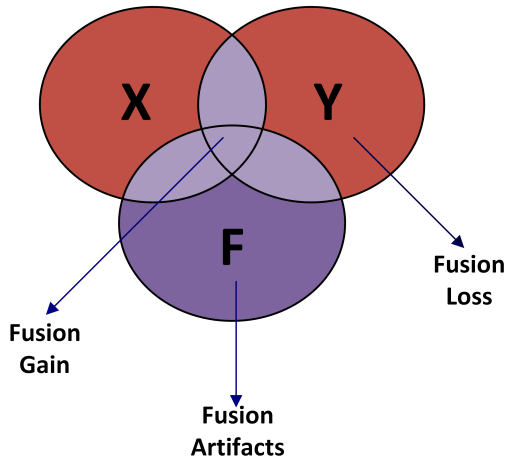


Fig. 3. (Xiao et al., 2020) Image Fusion concept using Venn diagram

2.2. Applications

2.2.1. Multi-Focus Image Fusion

In digital photography, individually captured images are partially focused on a particular region (Liu *et al.*, 2020; Bhat and Koundal, 2021). It is due to the limitations of any optical lens present in a camera. So combining these multiple partially focused images is essential to get better information for a particular scenario. This can be illustrated with the images shown in Fig. 4a, 4b, and 4c respectively. In this figure, the first image provides the clock's information from the foreground side, whereas the second one focuses on the background clock. None of these two images provides complete information, so combining essential regions using specific algorithms and the proper fusion rule of these two images will improve communication (Ma *et al.*, 2021; Tan

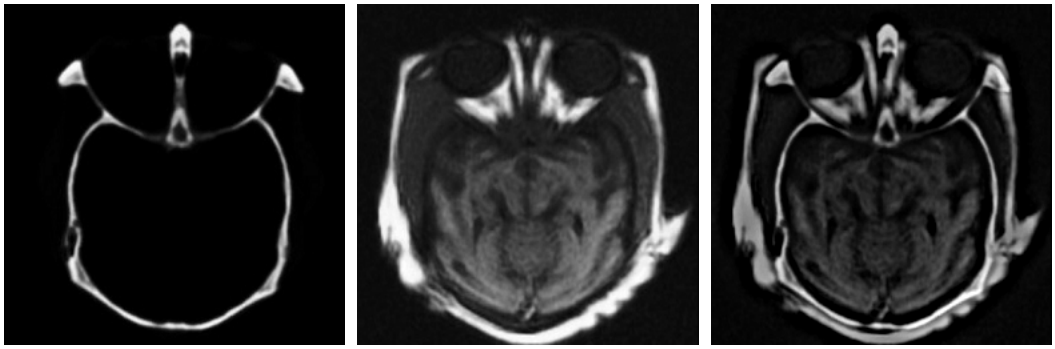
et al., 2021) as shown in the following image of Fig. 4c.

a *b* *c*

Fig. 4. (Datasets) a) Foreground Focused Image b) Background Focused Image c) Single Fused Image

2.2.2. Medical Image Fusion

In medical imaging, captured images of several modalities such as positron emission tomography (PET), single-photon emission tomography (SPECT), computer tomography (CT), and magnetic resonance imaging (MRI) are utilized to provide complementary information. As is evident, these individual images do not convey all of the necessary information (Du *et al.*, 2016; Tawfik *et al.*, 2020). Therefore, integration of these images is required into a single image. It can be illustrated in Fig. 5a, 5b, and 5c in which CT and MRI images of the human brain gives complementary information about the hard tissue and soft tissue, respectively. The figure shows that CT can capture bone structure or hard tissue information, whereas MRI can capture soft tissue information present in the brain. A fusion operation on these two images always helps radiologists for computer-assisted surgery and radiosurgery for better diagnosis and treatment (Li *et al.*, 2020).



a *b* *c*

Fig. 5. (Datasets) a) CT Image b) MRI Image c) Single Fused Image

2.2.3. Visible-Infrared Image Fusion

This type of image fusion is effectively used in military navigation, concealed weapon detection, and the images captured in low lighting or bad weather conditions (Kaur, Koundal and Kadyan, 2021; Li, Lin and Qu, 2021). As seen in Fig. 6a, the first image is visible in which three persons are visible, but this image does not provide any information about the weapon. While the other image in Fig. 6b is the infrared image in which the gun is visible, the decision regarding the face of the three-person remains unsolved. Therefore, a single fused image with more information must be generated to detect and locate the weapon using the complementary information from these two images (Xiao *et al.*, 2020).

a *b* *c*

Fig. 6. (Xiao et al., 2020) a) Visible Image b) Infrared Image c) Single Fused Image

2.3. Methodical Analysis

As per the methods available in the literature, image fusion can be categorized into two types based on the sensors employed in a particular system: 1) Single-sensor image fusion system (SSIF) and 2) Multi-sensor image fusion system (MSIF). In SSIF, multiple images are integrated into a single image taken by a single sensor only. While in the case of MSIF, multiple images are blended into a single image with the help of different imaging sensors (Xiao *et al.*, 2020). It can be seen in Fig. 7 and Fig. 8, respectively. These imaging sensors may be of different modalities. These two systems for any specific image fusion algorithm are attempted at pixel-level, feature-level, and decision-level in the spatial or transform domain.

2.3.1. Pixel-Level Image Fusion

In pixel-level image fusion, a pixel-wise operation is performed on source images. Human perception is given greater weight than computer vision at this level (Li *et al.*, 2017). This level can be further divided into spatial (single-scale) methods and transform (multi-scale) methods.

In the spatial domain category, fusion operation is performed directly on the source images or on the specific blocks of the source images. Therefore, the algorithms in this category can be considered as single-scale image fusion algorithms. Simple average, select max, select min, weighted average etc., are some basic mathematical operators that are directly implemented for fusion operation in this area (Xiao *et al.*, 2020). Besides these basic mathematical operations, some other methods based on principal component analysis (PCA) (*Principal component transform fusion method for TM and SAR images*), intensity-hue-saturation (HIS) (Tu *et al.*, 2001), independent component analysis (ICA) (Mitianoudis and Stathaki, 2007), focus-based measures (Huang and Jing, 2007; Tian *et al.*, 2011) are all such examples employed in the fusion process. Table 1 summarizes various approaches, along with potential advantages and disadvantages.

In the transform domain, the source images are first decomposed by using a proper transform function into sub-images. This step is known as the decomposition step, and the sub-images are also called transformed coefficients. As a result, fusion operation is performed on a specific fusion rule or principle on these transformed coefficients. Finally, these transformed coefficients are again reconstructed back into a single image. Therefore, this domain involves two additional steps, i.e., image decomposition and image reconstruction. This can be illustrated in Fig. 9. The algorithms under this domain can be further sub-categorized into three types: 1) Pyramid based methods, 2) Wavelet and other transform-based methods, and 3) Filtering based methods.

In pyramid based method, the source images are first decomposed into successive sub-images using some operations such as blurring and down sampling. Following that, the fusion rule is applied to the deconstructed sub-images, and then the fused image is reconstructed from the sub-images that have been fused together (reconstruction). For instance, if I_1 and I_2 are two source images, the decomposed sub-images may be represented as (Xiao *et al.*, 2020) :

$$\begin{aligned} \{C_p^{i+1}\}^1 &= [\{C_p^i(x,y)\}^1 * w(x,y)]_{\downarrow 2}, \\ \{C_p^{i+1}\}^2 &= [\{C_p^i(x,y)\}^2 * w(x,y)]_{\downarrow 2}, \; i = 0, 1, 2, ...N. \end{aligned} \tag{1}$$

where, $\{C_p^{i+1}\}^1$ represents sub-images gathered from pyramid decomposition of the source image I_1 at the $(i+1)^{th}$ level, which depends on its preceding level sub-image $\{C_p^i(x,y)\}^1$. Here * denotes the convolution operation, w is a linear filter, and N denotes the number of levels. The same is true for the source image I_2 as well. Then the pyramid is reconstructed back from these fused sub-

images to get the final fused image *F*.

In the multi-resolution category, discrete wavelet transform (DWT) decompositions are preferred over pyramid due to various advantages like fewer blocking effects, compact representation and directional information of a given image as compared to pyramid decomposition (Xiao *et al.*, 2020). In DWT, each source image is decomposed into wavelet coefficients at various levels, and by using various fusion rules, the coefficients are merged or fused accordingly. Finally, the fused image F is obtained by taking inverse discrete wavelet transform (IDWT) (Xiao *et al.*, 2020). The coefficients obtained from DWT are known as approximation [{C_{LL}}], horizontal [{C_{LH}}], vertical [{C_{HL}}], and diagonal [{C_{HH}}] respectively. It can be seen in Fig. 10.

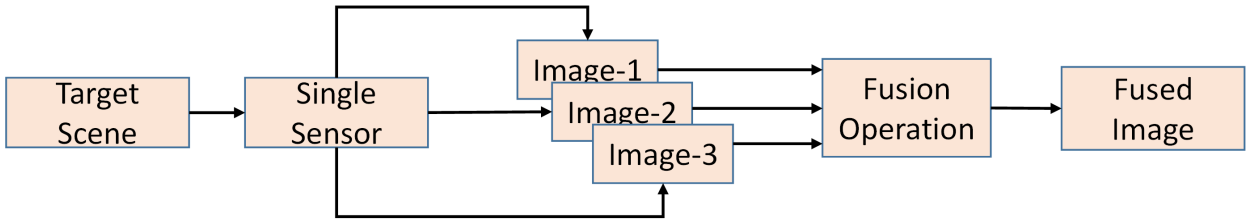


Fig. 7. (Xiao et al., 2020) SSIF System

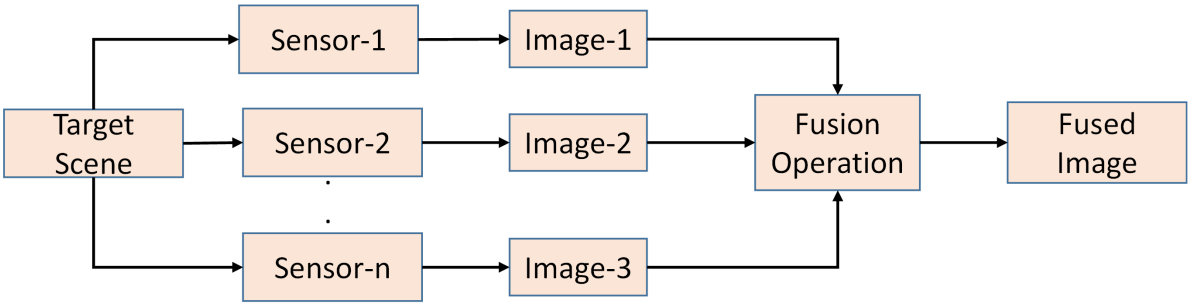


Fig. 8. (Xiao et al., 2020) MSIF System

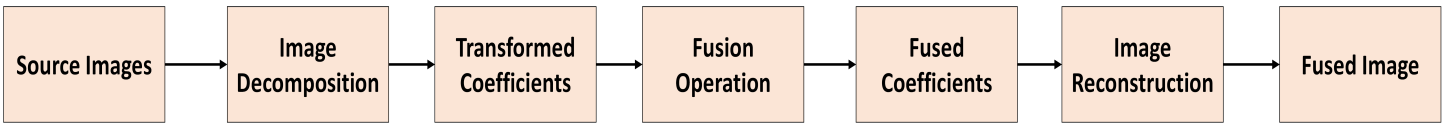


Fig. 9. (Xiao et al., 2020) Image Fusion process in transform-domain

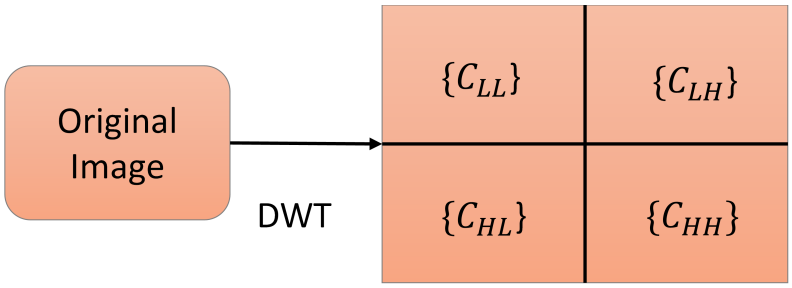


Fig. 10. (Xiao et al., 2020) The decomposition process through Discrete Wavelet Transform (DWT)

The techniques based on image filtering techniques in image fusion schemes are like edge-preserving decomposition filters (EPD) and non-EPD. For example, the average filter to perform the decomposition process. At first, the source images are decomposed into approximation or base layers that contain large-scale variations in intensity and detail layers that have small-scale variations in intensity. Then, a separate fusion rule is applied to these layers, and finally, a fused image is obtained by combining these two layers. Mathematically, the source images can be represented as (Xiao *et al.*, 2020):

$$\{B_n^{k+1}\}_{n=1}^{2} = \{B_n^{k}\}_{n=1}^{2} * w, \tag{2}$$

where, k = 0, 1, 2, ……, K and B_n^{k+1} is the base layer of nth source image at k+1 level, which depends on the previous level base layer B_n^k. Here * operator denotes the convolution operation, and w is an image filter. The detail layers at the present level are obtained by subtracting the base layers of the previous level from the base layers of the present level, which can be represented as (Xiao *et al.*, 2020):

$$D_n^{k+1} = B_n^{k+1} - B_n^{k}. \tag{3}$$

Table 2 provides the summary of these methods along with the advantages and disadvantages.

2.3.2. Feature-Level Image Fusion

The fundamental image characteristics such as edges, corners, lines, and other components are examined for feature-level image fusion techniques (Xiao *et al.*, 2020). Compared to pixel-level image fusion techniques, this fusion level results in high information loss but is more effective in real-time applications. The fusion operation in this level is generally followed in four steps: information acquisition, information processing, feature extraction, and information fusion

(Barron and Thomas, 2001; Xiao *et al.*, 2020).

Table 1. An Overview of Spatial Domain Methods

Single Scale Methods (Spatial domain)	**Advantages**	**Disadvantages**
Average, minimum, maximum, and morphological (Ardheshir and Nikolov) (Ardeshir Goshtasby and Nikolov, 2007; Li *et al.*, 2017) operators	Simple to implement	Reduce contrast, or create brightness or RGB distortions
Principal component analysis (PCA) (*Principal component transform fusion method for TM and SAR images*), independent component analysis (ICA) (Mitianoudis and Stathaki, 2007)), intensity-hue-saturation (IHS) (Tu *et al.*, 2001)	Efficient in terms of computation	Spectral distortion is possible, and only a small number of fusion datasets will generate satisfactory conclusions
Focus measure (Huang and Jing (Huang and Jing, 2007)), bilateral sharpness criteria (Tian *et al.*, 2011)	May have a constructive effect on outcomes	Only applicable to a small number of datasets, and it is expensive to implement
Optimization methods (Shen *et al.*, 2011), Xu and Varshney (Xu, Chen and Varshney, 2011)	May produce desirable outcomes	It requires a large number of iterations. It is complex and expensive to compute with over smoothed merged image

Table 2. An overview of Transform-Domain Methods

Multi-Scale Decomposition methods	Advantages	Disadvantages
Laplacian/Gaussian pyramid (Burt and Adelson, 1983) Low pass pyramid ratio (Toet, 1989) Morphological pyramid (Toet, 1989) Gradient pyramid (Xiao *et al.*, 2020)	Provides better image quality of a representation for multi-focus images.	Provide almost the same result. The number of breakdown levels affects the IF results. Possibility of halo effects near edges.
Discrete cosine transform (DCT) (Naidu, 2012; Shreyamsha Kumar, 2012)	Decomposed images into series of waveforms and used for real-time applications.	Low quality fused image.
Discrete wavelet transform (Li, Manjunath and Mitra, 1995; Wilson, 1997)	Produced better quality of fused image with good SNR. Reduced the spectral distortion and fewer blocking effects.	Merged image has fewer spatial resolutions.
Stationary wavelet transform (SWT) (Jiang *et al.*, 2017; Jin *et al.*, 2018; Ganasala and Prasad, 2020)	Give better result at level 2 of decomposition.	Time-consuming process.
Curvelet Transform (Li and Yang, 2008)	Suitable for real-time applications.	Very time-consuming process.
Kekre's hybrid wavelet transform (Kekre, Sarode and Dhannawat, 2012; Palkar and Mishra, 2019)	Provide better results.	It cannot be used for the integer of power of two.
Hilbert vibration decomposition (HVD) (Saxena and Sharma, 2016, 2017)	Provides good results for specific image database.	The fusion process is in 1-D.
Sparse representation (Zhang *et al.*, 2018)	Stable and suitable for practical applications.	Misregistration among source images.
Filtering (Li, Kang and Hu, 2013; Shreyamsha Kumar, 2013; Zhao *et al.*, 2013; Jiang and Wang, 2014; Cui *et al.*, 2015; Gan *et al.*, 2015)	Provides desirable decomposition with edge preservation.	High computational time in some methods.

2.3.3. Decision-Level Image Fusion

The information loss is highest at the decision-level image fusion, but the obtained results are more accurate and flawless than the other two schemes. The methods adopted in this category is performed in four steps: multi-sensor image processing, decision generation, convergence in the fusion center, and fusion conclusion (Gunatilaka and Baertlein, 2001). In addition, voting, Bayes inference, evidence theory, fuzzy integrals, including ICA and support vector machine (SVM) etc., are some commonly used methods in this approach (Xiao *et al.*, 2020). Table 3 highlights the comparison of the three approaches previously mentioned.

Table 3. A comparative overview of pixel-level, feature-level, and decision-level image fusion

Method	Level	Advantages	Disadvantages
Pixel-level	Low	Ease of implementation, low loss of data.	Poor results if affected by noise.
Feature-level	Intermediate	Effective in real-time processing.	High loss of data as compared to pixel-level.
Decision-level	High	More accurate and effective in real-time processing.	Information loss is the highest.

Apart from the above-reviewed methods, which can be considered traditional methods, artificial intelligence is gaining much attention in recent times and has attracted researchers in this field with various applications. As a result, image fusion is also one of the applications in which the concept of machine learning and deep learning is thoroughly used (Xiao *et al.*, 2020). Moreover, this approach is applicable both in the spatial and the transform domain (Liu *et al.*, 2018; Xiao *et al.*, 2020; Li *et al.*, 2021).

3. Justification for Selection of Research Area

- According to the literature, multi-scale decomposition approaches offer specific improvements over single-scale decomposition techniques, such as improved information feature extraction in terms of edges and lines. So it will be interesting to investigate and find out the results by developing different latest multi-scale decomposition based image fusion algorithms that are yet to be explored.

- As per Fig. 3, some noise and visual artifacts may come in the output/fused image in image fusion. However, in the pre-processing step of image fusion, noise and visual artifacts can be removed or minimized using image enhancement techniques under multi-scale decomposition. As a result, this stage may be helpful for improved visual information, which is yet to be studied.

- The concept of image fusion using the combination of different multi-scale decomposition techniques can be considered as the hybrid approach is significantly less developed. As a result, this hybrid method that makes use of the critical properties of various multi-scale decompositions might be beneficial for image fusion.

- In recent years, artificial intelligence (machine learning and deep learning) has received a lot of attention in every sector, attracting a lot of academics and experts. In the case of image fusion, the above points will provide in-depth investigations for academicians and researchers working in this field.

- The concept of image fusion is applicable for many diverse fields such as multi-focus, multi-modal medical, remote sensing, visible-infrared, concealed weapon detection etc. Therefore, the positive change in the results computed using the above facts will improve all these applications.

4. Objectives of the Study

- To study and simulate the novel image fusion techniques for different applications. Compute and compare the several objective fusion metrics.

- To study and simulate the novel image enhancement techniques on the different sets of images and apply novel image fusion techniques after enhancement for various applications. Furthermore, compute and compare the different objective fusion metrics by considering both with enhancement and without enhancement as a pre-processing stage.

- To develop and simulate the novel image enhancement technique under multi-scale decomposition that should be effective on the different sets of images captured under different environmental conditions. Furthermore, compute and compare the various parameters related to image enhancement with the already existing novel techniques.

- To develop and simulate the novel image fusion technique with the novel image enhancement technique as stated above as a pre-processing stage under multi-scale decomposition. Compute and compare the different objective fusion metrics with the already existing novel fusion metrics.

- To develop and simulate the novel image fusion technique with the hybrid approach under multi-scale decomposition. Compute and compare the objective fusion metrics with and without enhancement as a pre-processing stage with the already existing novel image fusion techniques.

5. Methodology

a) Literature Survey: The existing novel image fusion approaches in spatial (single-scale) and transform (multi-scale) domains.

b) Simulation of existing novel techniques for image fusion with image enhancement as a pre-processing stage using MATLAB R2020 software for different applications in both spatial domain and transform domain and detail study of the various objective fusion metrics.

c) Implementing and developing a new image enhancement technique under multi-scale decomposition and simulate it using MATLAB R2020 software.

d) Use the enhanced images obtained in c) as a pre-processing stage, and implement & develop new image fusion technique for different applications under multi-scale decomposition with simulation using MATLAB R2020 software and detail study of different objective fusion metrics such as:

- **Mean**

This value gives the measurement of the index of the contrast and is given as (Xiao *et al.*, 2020):

$$\overline{F} = \sum_{i=1}^{M}\sum_{j=1}^{N} F(i,j) / M \times N, \tag{4}$$

where, $M \times N$ represents the size of the fused image F and $F(i,j)$ corresponds to the pixel intensity.

- **Standard Deviation**

This evaluation metric is used to measure the richness of image information. It is defined for fused image F as (Xiao *et al.*, 2020):

$$SD = \sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N} (F(i,j) - \overline{F})^2 / M \times N}, \tag{5}$$

where, $\overline{F}$ is the average pixel value and $F(i,j)$ corresponds to the pixel intensity value of the fused image F.

- **Mutual Information**

Mutual information generally measures the similarity between the fused image and the input image in grayscale distribution, i.e., the amount of information in the fused image. It is defined as (Xiao *et al.*, 2020):

$$I_{FX}(f,x)=\sum_{f,x} p_{FX}(f,x)\log_2[p_{FX}(f,x)/\,p_F(f)p_X(x)]. \tag{6}$$

The above equation determined the mutual information of source image X concerning fused image F. In a similar way, we can find the mutual information for source image Y by using this equation, and after adding these two, we get the general mutual information which is given as (Xiao *et al.*, 2020):

$$M_{XY}^{F}=I_{FX}(f,x)+I_{FY}(f,y). \tag{7}$$

- **Edge Information**

It was proposed as a fused image quality evaluation metrics based on edge information to measure the fusion image quality by evaluating the edge information transfer amount from the source image to the fused image. This can be expressed as (Xiao *et al.*, 2020):

$$Q^{XY}(i,j)=Q_g^{XY}(i,j).Q_\alpha^{XY}(i,j), \tag{8}$$

where, $Q_g^{XY}(i,j)$ and $Q_\alpha^{XY}(i,j)$ are image X and Y edge width and direction of the similarity, respectively.

$$Q_g^{XY}=\Big/_{1+e^{\kappa_g(G^{XY}(i,j)-\sigma_g)}}^{\Gamma_g}, \tag{9}$$

$$Q_\alpha^{XY}=\Big/_{1+e^{\kappa_\alpha(A^{XY}(i,j)-\sigma_\alpha)}}^{\Gamma_\alpha}, \tag{10}$$

where $\Gamma_g,\kappa_g,\sigma_g,\Gamma_\alpha,\kappa_\alpha,\sigma_\alpha$ are all constants, G^{XY} and A^{XY} are the relative edge strength and edge direction of X relative to Y, respectively. For this, the formula is:

$$G^{XY}(i,j)=\begin{cases}\Big/_{g_Y(i,j)}^{g_X(i,j)}, g_X(i,j)<g_Y(i,j)\\ \Big/_{g_X(i,j)}^{g_Y(i,j)}, g_X(i,j)\geq g_Y(i,j)\end{cases}, \tag{11}$$

$$A^{XY}(i,j)=\Big/_{\frac{\pi}{2}}^{|\,|\alpha_X(i,j)-\alpha_Y(i,j)|-\frac{\pi}{2}|}, \tag{12}$$

Finally, the quality evaluation result of the fused image F can be obtained by using the equation which is given as (Xiao *et al.*, 2020):

$$Q_{XY}^{F}=(\sum_{i=1}^{M}\sum_{j=1}^{N}(Q^{XF}(i,j)\omega^{X}(i,j)+Q^{YF}(i,j)\omega^{Y}(i,j)))/\sum_{i=1}^{M}\sum_{j=1}^{N}(\omega^{X}(i,j)+\omega^{Y}(i,j)), \quad (13)$$

where, $\omega^{X}(i,j)$ and $\omega^{Y}(i,j)$ are the weights of $Q^{XF}(i,j)$ and $Q^{YF}(i,j)$, respectively.

- **Entropy**

Information entropy (IE) is used to measure the degree of information abundance in the fused image and acts as a measure of image fusion quality. It is defined as (Xiao *et al.*, 2020):

$$IE=-\sum_{i=0}^{L-1}p_{F}(i)\log_{2}p_{F}(i), \quad (14)$$

where, $p_{F}(i)$ is the proportion of pixels with grey level *i* in the image ***F***. L is the gray level, which is generally taken as 256.

- **Average Gradient**

For quantitative analysis, the average gradient is expressed as (Xiao *et al.*, 2020):

$$AG(F)=\sum_{i=1}^{M-1}\sum_{j=1}^{N-1}\sqrt{[(\Delta_{x}F(i,j)^{2})+(\Delta_{y}F(i,j)^{2})]/2}\Big/(M-1)(N-1), \quad (15)$$

where, $\Delta_{x}F(i,j)=F(i,j)-F(i+1,j),\Delta_{y}F(i,j)=F(i,j)-F(i,j+1)$.

- **Spatial Frequency**

The spatial frequency reflects the rate of change of the image gray which is given as (Xiao *et al.*, 2020):

$$SF(F)=\sqrt{RF^{2}+CF^{2}}, \quad (16)$$

where, RF and CF are the row frequency and column frequency of F which can be represented as:

$$RF=\sqrt{\left[\sum_{i=1}^{M-1}\sum_{j=1}^{N-1}((F(i,j)-F(i,j+1))^{2}\right]\Big/MN}, \quad (17)$$

$$CF=\sqrt{\left[\sum_{i=1}^{M-1}\sum_{j=1}^{N-1}((F(i,j)-F(i+1,j))^{2}\right]\Big/MN}. \quad (18)$$

- **Peak Signal to Noise Ratio (PSNR)**

Mathematically, PSNR is given as:

$$PSNR = 10\log(255^2 / MSE), \tag{19}$$

where, MSE is the mean square error for the corresponding images.

The above process is illustrated in Fig. 10.

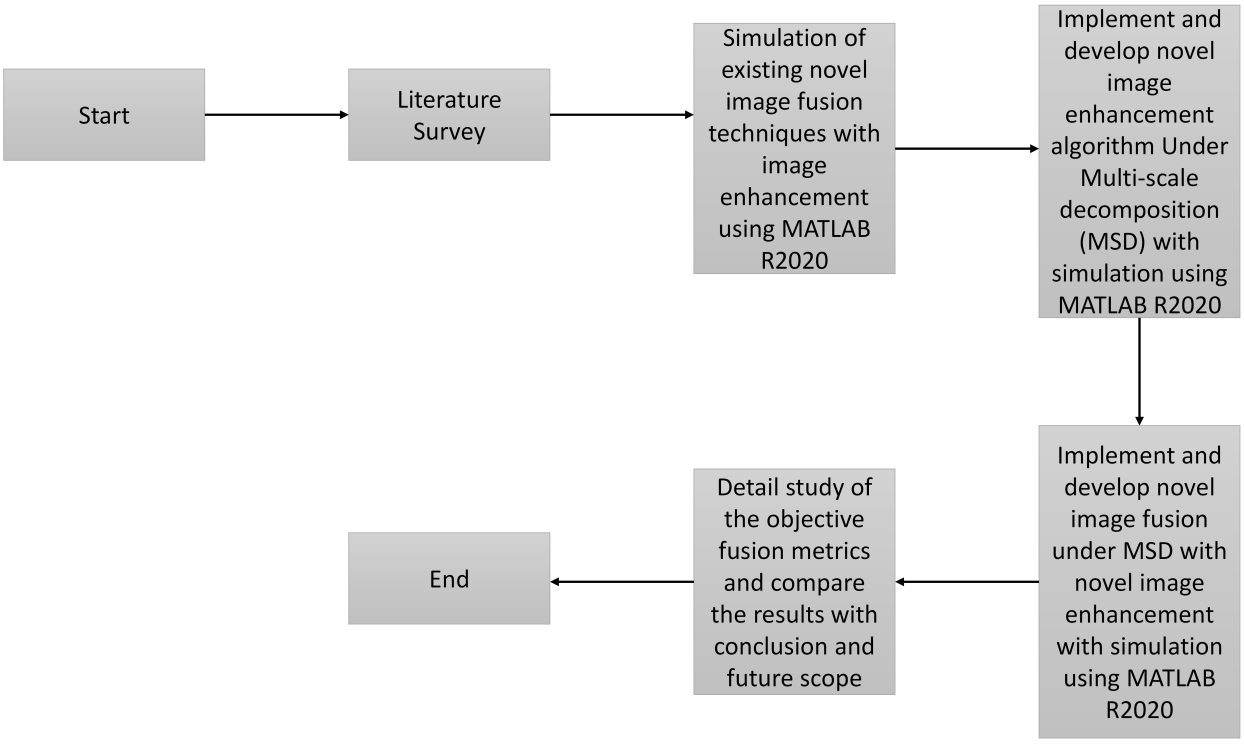

Start
Literature Survey
Simulation of existing novel image fusion techniques with image enhancement using MATLAB R2020
Implement and develop novel image enhancement algorithm Under Multi-scale decomposition (MSD) with simulation using MATLAB R2020
Implement and develop novel image fusion under MSD with novel image enhancement with simulation using MATLAB R2020
Detail study of the objective fusion metrics and compare the results with conclusion and future scope
End

Fig. 11. Block diagram of the methodology

6. Expected Outcomes

- One of the primary projected outcomes of this research plan is developing a novel approach in image fusion based on multi-scale decomposition for various applications.
- With this new technique, several quantitative parameters, i.e., objective fusion metrics such as entropy, mean, standard deviation, edge information, average gradient, spatial frequency, psnr, etc., will be analyzed and compared with the existing techniques for its performance.
- Publishing the work in the peer-reviewed journal of international repute (Web of Science/Scopus).
- Contribution towards vision: Better visual information and communication for different disciplines such as multi-focus, medical imaging, infrared-visible, etc.

7. Work Plan/ Time Lines

Table 4. Tentative Work Plan/Time Line

Research Activity	6 Months	12 Months	18 Months	24 Months	30 Months	36 Months	*
Course Work							
Literature Survey							
Methodology Steps							
Quarterly Reports							
Communication of Papers							
Preparation of Final Thesis							
Submission of Thesis							

***As Approved Extension**

8. References

Ardeshir Goshtasby, A. and Nikolov, S. (2007) 'Image fusion: Advances in the state of the art', *Information Fusion*, 8(2), pp. 114–118. doi: 10.1016/J.INFFUS.2006.04.001.

Azarang, A. and Kehtarnavaz, N. (2021) *Image Fusion in Remote Sensing*. Morgan & Claypool. doi: 10.2200/S01074ED1V01Y202101IVM021.

Barron, D. R. and Thomas, O. D. J. (2001) 'Image fusion through consideration of texture components', *Electronics Letters*, 37(12), pp. 746–748. doi: 10.1049/EL:20010536.

Bhat, S. and Koundal, D. (2021) 'Multi-focus image fusion techniques: a survey', *Artificial Intelligence Review*, 54, pp. 5735–5787. doi: 10.1007/S10462-021-09961-7.

Burt, P. J. and Adelson, E. H. (1983) 'The Laplacian Pyramid as a Compact Image Code', *IEEE Transactions on Communications*, 31(4), pp. 532–540. doi: 10.1109/TCOM.1983.1095851.

Chaudhuri, S. and Kotwal, K. (2014) *Hyperspectral Image Fusion*. Springer. doi: 10.1007/978-1-4614-7470-8.

Cui, G. *et al.* (2015) 'Detail preserved fusion of visible and infrared images using regional saliency extraction and multi-scale image decomposition', *Optics Communications*, 341, pp. 199–209. doi: 10.1016/J.OPTCOM.2014.12.032.

Datasets (no date). Available at: https://sites.google.com/view/durgaprasadbavirisetti/datasets (Accessed: 5 December 2021).

Du, J. *et al.* (2016) 'An overview of multi-modal medical image fusion', *Neurocomputing*, 215, pp. 3–20. doi: 10.1016/j.neucom.2015.07.160.

Feldman, M. (2008) 'Theoretical analysis and comparison of the Hilbert transform decomposition methods', *Mechanical Systems and Signal Processing*, 22(3), pp. 509–519. doi: 10.1016/J.YMSSP.2007.09.013.

Feng, Z., Zhang, D. and Zuo, M. J. (2017) 'Adaptive Mode Decomposition Methods and Their Applications in Signal Analysis for Machinery Fault Diagnosis: A Review with Examples', *IEEE*

Access, 5, pp. 24301–24331. doi: 10.1109/ACCESS.2017.2766232.

Van Fleet, P. J. (2019) 'The Haar Wavelet Transformation', in *Discrete Wavelet Transformations*. John Wiley & Sons, Inc., pp. 125–181. doi: 10.1002/9781119555414.CH4.

Gan, W. *et al.* (2015) 'Infrared and visible image fusion with the use of multi-scale edge-preserving decomposition and guided image filter', *Infrared Physics & Technology*, 72, pp. 37–51. doi: 10.1016/J.INFRARED.2015.07.003.

Ganasala, P. and Prasad, A. D. (2020) 'Medical image fusion based on laws of texture energy measures in stationary wavelet transform domain', *International Journal of Imaging Systems and Technology*, 30(3), pp. 544–557. doi: 10.1002/IMA.22393.

Gunatilaka, A. H. and Baertlein, B. A. (2001) 'Feature-level and decision-level fusion of noncoincidently sampled sensors for land mine detection', *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 23(6), pp. 577–589. doi: 10.1109/34.927459.

Huang, W. and Jing, Z. (2007) 'Evaluation of focus measures in multi-focus image fusion', *Pattern Recognition Letters*, 28(4), pp. 493–500. doi: 10.1016/J.PATREC.2006.09.005.

Image fusion (Topic) – 40,076 – Web of Science Core Collection (no date). Available at: https://www.webofscience.com/wos/woscc/summary/34c3aad5-41c9-42d6-a901-2775835ce8b9-0caa1542/relevance/1 (Accessed: 12 October 2021).

Jiang, D. and Kim, J. (2021) 'Image Retrieval Method Based on Image Feature Fusion and Discrete Cosine Transform', *Applied Sciences*, 11(12), pp. 5701-5727. doi: 10.3390/APP11125701.

Jiang, Q. *et al.* (2017) 'A Novel Multi-Focus Image Fusion Method Based on Stationary Wavelet Transform and Local Features of Fuzzy Sets', *IEEE Access*, 5, pp. 20286–20302. doi: 10.1109/ACCESS.2017.2758644.

Jiang, Y. and Wang, M. (2014) 'Image fusion using multiscale edge-preserving decomposition based on weighted least squares filter', *IET Image Processing*, 8(3), pp. 183–190. doi: 10.1049/IET-IPR.2013.0429.

Jin, X. *et al.* (2018) 'Infrared and visual image fusion method based on discrete cosine transform and local spatial frequency in discrete stationary wavelet transform domain', *Infrared Physics & Technology*, 88, pp. 1–12. doi: 10.1016/J.INFRARED.2017.10.004.

Kaur, H., Koundal, D. and Kadyan, V. (2021) 'Image Fusion Techniques: A Survey', *Archives of Computational Methods in Engineering*, 1, pp. 1–23. doi: 10.1007/S11831-021-09540-7.

Kekre, H. B., Sarode, T. and Dhannawat, R. (2012) 'Image fusion using Kekre's hybrid wavelet transform', in *Proceedings - 2012 International Conference on Communication, Information and Computing Technology, ICCICT 2012*. doi: 10.1109/ICCICT.2012.6398225.

Li, G., Lin, Y. and Qu, X. (2021) 'An infrared and visible image fusion method based on multi-scale transformation and norm optimization', *Information Fusion*, 71, pp. 109–129. doi: 10.1016/J.INFFUS.2021.02.008.

Li, H., Manjunath, B. S. and Mitra, S. K. (1995) 'Multisensor Image Fusion Using the Wavelet Transform', *Graphical Models and Image Processing*, 57(3), pp. 235–245. doi: 10.1006/GMIP.1995.1022.

Li, S. *et al.* (2017) 'Pixel-level image fusion: A survey of the state of the art', *Information Fusion*, 33, pp. 100–112. doi: 10.1016/J.INFFUS.2016.05.004.

Li, S., Kang, X. and Hu, J. (2013) 'Image fusion with guided filtering', *IEEE Transactions on Image Processing*, 22(7), pp. 2864–2875. doi: 10.1109/TIP.2013.2244222.

Li, S. and Yang, B. (2008) 'Multifocus image fusion by combining curvelet and wavelet transform', *Pattern Recognition Letters*, 29(9), pp. 1295–1301. doi: 10.1016/J.PATREC.2008.02.002.

Li, X. *et al.* (2020) 'Laplacian Redecomposition for Multimodal Medical Image Fusion', *IEEE Transactions on Instrumentation and Measurement*, 69(9), pp. 6880–6890. doi: 10.1109/TIM.2020.2975405.

Li, Y. *et al.* (2021) 'Medical image fusion method by deep learning', *International Journal of Cognitive Computing in Engineering*, 2, pp. 21–29. doi: 10.1016/J.IJCCE.2020.12.004.

Liang, J. *et al.* (2012) 'Image fusion using higher order singular value decomposition', *IEEE Transactions on Image Processing*, 21(5), pp. 2898–2909. doi: 10.1109/TIP.2012.2183140.

Liu, Y. *et al.* (2018) 'Deep learning for pixel-level image fusion: Recent advances and future prospects', *Information Fusion*, 42, pp. 158–173. doi: 10.1016/J.INFFUS.2017.10.007.

Liu, Y. *et al.* (2020) 'Multi-focus image fusion: A Survey of the state of the art', *Information Fusion*, 64, pp. 71–91. doi: 10.1016/j.inffus.2020.06.013.

Ma, J. *et al.* (2021) 'SMFuse: Multi-Focus Image Fusion Via Self-Supervised Mask-Optimization', *IEEE Transactions on Computational Imaging*, 7, pp. 309–320. doi: 10.1109/TCI.2021.3063872.

Mitchell, H. B. (2015) *Image Fusion*, *Radiologic technology*. Springer. doi: 10.4135/9781412939591.n611.

Mitianoudis, N. and Stathaki, T. (2007) 'Pixel-based and region-based image fusion schemes using ICA bases', *Information Fusion*, 8(2), pp. 131–142. doi: 10.1016/J.INFFUS.2005.09.001.

Naidu, V. P. S. (2012) 'Discrete Cosine Transform based Image Fusion Techniques', *Journal Of Communication*, *Navigation and Signal Processing*, 1(1), pp. 35–45.

Palkar, B. and Mishra, D. (2019) 'Fusion of multi-modal lumbar spine images using Kekre's hybrid wavelet transform', *IET Image Processing*, 13(12), pp. 2271–2280. doi: 10.1049/iet-ipr.2018.5609.

Principal component transform fusion method for TM and SAR images (no date). Available at: http://www.rsta.ac.cn/CN/10.11873/j.issn.1004-0323.1998.1.46 (Accessed: 13 October 2021).

Saxena, N. and Sharma, K. K. (2016) 'Hilbert vibration decomposition based image fusion', *Electronics Letters*, 52(19), pp. 1605–1607. doi: 10.1049/EL.2016.2270.

Saxena, N. and Sharma, K. K. (2017) 'Pansharpening approach using Hilbert vibration decomposition', *IET Image Processing*, 11(12), pp. 1152–1162. doi: 10.1049/iet-ipr.2017.0133.

Saxena, N. and Sharma, K. K. (2018) 'Pansharpening scheme using filtering in two-dimensional

discrete fractional Fourier transform', *IET Image Processing*, 12(6), pp. 1013–1019. doi: 10.1049/IET-IPR.2017.0961.

Shen, R. *et al.* (2011) 'Generalized random walks for fusion of multi-exposure images', *IEEE Transactions on Image Processing*, 20(12), pp. 3634–3646. doi: 10.1109/TIP.2011.2150235.

Shreyamsha Kumar, B. K. (2012) 'Multifocus and multispectral image fusion based on pixel significance using discrete cosine harmonic wavelet transform', *Signal*, *Image and Video Processing*, 7(6), pp. 1125–1143. doi: 10.1007/S11760-012-0361-X.

Shreyamsha Kumar, B. K. (2013) 'Image fusion based on pixel significance using cross bilateral filter', *Signal*, *Image and Video Processing*, 9(5), pp. 1193–1204. doi: 10.1007/S11760-013-0556-9.

Tan, J. *et al.* (2021) 'Multi-focus image fusion with Geometrical Sparse Representation', *Signal Processing: Image Communication*, 92, p. 116130. doi: 10.1016/J.IMAGE.2020.116130.

Tawfik, N. *et al.* (2020) 'Survey study of multimodality medical image fusion methods', *Multimedia Tools and Applications*, 80(4), pp. 6369–6396. doi: 10.1007/S11042-020-08834-5.

Thiagarajan, J. J. *et al.* (2014) *Image understanding using sparse representations*, *Synthesis Lectures on Image*, *Video*, *and Multimedia Processing*. Morgan and Claypool Publishers. doi: 10.2200/S00563ED1V01Y201401IVM015.

Tian, J. *et al.* (2011) 'Multi-focus image fusion using a bilateral gradient-based sharpness criterion', *Optics Communications*, 284(1), pp. 80–87. doi: 10.1016/J.OPTCOM.2010.08.085.

Toet, A. (1989) 'A morphological pyramidal image decomposition', *Pattern Recognition Letters*, 9(4), pp. 255–261. doi: 10.1016/0167-8655(89)90004-4.

Toet, A. (1989) 'Image fusion by a ratio of low-pass pyramid', *Pattern Recognition Letters*, 9(4), pp. 245–253. doi: 10.1016/0167-8655(89)90003-2.

Tu, T. M. *et al.* (2001) 'A new look at IHS-like image fusion methods', *Information Fusion*, 2(3), pp. 177–186. doi: 10.1016/S1566-2535(01)00036-7.

Wilson, T. A. (1997) ‘Perceptual-based image fusion for hyperspectral data’, *IEEE Transactions on Geoscience and Remote Sensing*, 35(4), pp. 1007–1017. doi: 10.1109/36.602543.

Xiao, G. *et al.* (2020) ‘Decision-Level Image Fusion’, in *Image Fusion*. Springer Singapore, pp. 149–170. doi: 10.1007/978-981-15-4867-3_4.

Xiao, G. *et al.* (2020) ‘Feature-Level Image Fusion’, in *Image Fusion*. Springer Singapore, pp. 103–147. doi: 10.1007/978-981-15-4867-3_3.

Xiao, G. *et al.* (2020) *Image fusion*. Springer. doi: 10.1007/978-981-15-4867-3.

Xiao, G. *et al.* (2020) ‘Image Fusion Based on Machine Learning and Deep Learning’, in *Image Fusion*. Springer Singapore, pp. 325–352. doi: 10.1007/978-981-15-4867-3_7.

Xiao, G. *et al.* (2020) ‘Introduction to Image Fusion’, in *Image Fusion*. Springer Singapore, pp. 3–20. doi: 10.1007/978-981-15-4867-3_1.

Xiao, G. *et al.* (2020) ‘Pixel-Level Image Fusion’, in *Image Fusion*. Springer Singapore, pp. 21–101. doi: 10.1007/978-981-15-4867-3_2.

Xu, M., Chen, H. and Varshney, P. K. (2011) ‘An image fusion approach based on markov random fields’, *IEEE Transactions on Geoscience and Remote Sensing*, 49(12 PART 2), pp. 5116–5127. doi: 10.1109/TGRS.2011.2158607.

Zhang, H. *et al.* (2021) ‘Image fusion meets deep learning: A survey and perspective’, *Information Fusion*, 76, pp. 323–336. doi: 10.1016/J.INFFUS.2021.06.008.

Zhang, Q. *et al.* (2018) ‘Sparse representation based multi-sensor image fusion for multi-focus and multi-modality images: A review’, *Information Fusion*, 40, pp. 57–75. doi: 10.1016/j.inffus.2017.05.006.

Zhao, J. *et al.* (2013) ‘Detail enhanced multi-source fusion using visual weight map extraction based on multi scale edge preserving decomposition’, *Optics Communications*, 287, pp. 45–52. doi: 10.1016/J.OPTCOM.2012.08.070.